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Tail Dependence Between US and Chinese Technology Stocks Under Policy and Technological Shocks

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ABSTRACT
The financial market is a complex and interconnected system, and the correlation between the U.S. and Chinese stock markets has long been a focal point in financial research. However, limited attention has been paid specifically to the technology sector. This paper selects the Hang Seng TECH Index and the NASDAQ Composite Index as the representative benchmarks for the Chinese and U. S. technology markets. We first model the marginal distributions of return series using the t-GARCH(1, 1) framework and compute constant upper and lower tail dependence coefficients. Then, we estimate the parameters of the SJC Copula using a two-step estimation procedure. Finally, we conduct independent and synergistic effect tests to examine how the two events influence the tail dependence structure between the two markets. The results reveal asymmetric and time-varying tail dependence dynamics, with the policy shock inducing a sustained increase and the technological shock triggering a short-lived spike in extreme market co-movements.

KEYWORDS
Tail dependence; GARCH-t; SJC Copula; Technology; Time-varying

1 Introduction

Technology firms in China and the United States have become central targets for international capital allocation. However, their high sensitivity to policy changes often leads to extreme market conditions, exerting profound impacts on the financial system and even the real economy. When assessing asset correlations under such extreme scenarios, tail dependence provides a more accurate measure of extreme co-movements between asset returns, thereby offering critical insight into tail risk exposure.

2 Literature review

Previous studies have frequently adopted the Copula function framework proposed by Sklar (1959) to characterize tail dependence structures among multivariate random variables. Among commonly used Copula functions, the Normal Copula and the Student's t Copula are suitable only for symmetric tail dependence (Li, 1999; Demarta & McNeil, 2005)[1][2]. In contrast, the Gumbel Copula and the Clayton Copula capture only upper and lower tail dependence, respectively (Émile & Gumbel, 1960; Clayton, 1978) [3][4]. This study employs the Symmetrized Joe-Clayton (SJC) Copula developed by Patton (2006), which is a symmetrized version of the Joe-Clayton Copula (Joe, 1997), capable of capturing asymmetric dependence[6].

The estimation of Copula functions relies on the marginal distributions of time series. Engle (1982) introduced the ARCH model to capture volatility clustering in financial time series, but it performs poorly with small sample sizes due to parameter instability. Bollerslev (1986) extended this to the GARCH model by incorporating lagged conditional variance terms as explanatory variables, and later proposed GARCH-t model to account for returns with heavy tails (Bollerslev, 1987) [7]. Numerous empirical studies have validated the effectiveness of GARCH-t models. For example, Connolly (1989) recommended using the GARCH-t model for studying extreme events in the stock market, successfully applying it to investigate the “day-of-the-week effects” in U.S. equities[8]. Furthermore, Gu, Chen, and Zhou (2008) found that micro-level returns in the Chinese stock market follow an inverse cubic law and tend to approximate a Student's t-distribution after aggregation[9]. According to Yang Longjiang (2021), the GARCH(1, 1)-t specification is well-suited for modeling the marginal return distributions of 19 industry sectors in China's Shanghai and Shenzhen stock exchanges[10].

A widely used approach in recent literature is to first estimate marginal distributions using the GARCH-t model and then apply Copula functions to analyze tail dependence between markets. Zhang and Wei (2004) developed a Copula-t-GARCH model and found strong positive correlation among different stock indices despite heterogeneous marginal distributions, demonstrating the advantage of Copula models in capturing dependence structures[11]. Other studies have applied the GARCH(1, 1)-t and SJC Copula models to investigate tail dependence in various contexts. For instance, Wen, Yang, and Zhou (2019) studied the dependence across oil[12] and stock markets, Song (2021) analyzed tail dependence among global equity markets[13], and Jia et al. (2025) examined tail dependence across industry-specific indices under climate change, respectively[14].

Despite the widespread application of the GARCH(1,1)-t and SJC Copula models, few studies have specifically focused on the dynamic tail dependence in the U.S. and Chinese technology stock markets. Moreover, existing research tends to examine the effects of single or homogeneous types of events, lacking a comprehensive framework to evaluate the combined effects of heterogeneous shocks.

This study focuses on two major events—policy changes and technological breakthroughs—to investigate how the sequencing and interaction of these events influence the evolution of tail dependence. We analyze their independent and joint effects. Additionally, we assess the applicability of the time-varying SJC Copula-GARCH-t model in capturing tail risks in high-volatility assets such as technology stocks. By doing so, we contribute a new industry-specific case to the literature on tail risk modeling and fill a gap in research on tech-sector tail co-movements.

3 Method

To investigate the independent and joint effects of policy shocks and technological shocks on the tail dependence between U. S. and Chinese technology stock markets, we first estimate marginal distribution models for each index, quantifying the immediate impact of each event on the volatility of individual markets. Based on the chronological sequence of these events, we then divide the sample into three sub-periods to capture potential regime shifts in tail dependence during the event windows.

3.1 Model framework

According to Sklar's Theorem, the joint distribution of two return series can be expressed in terms of their marginal cumulative distributions and a Copula function, as follows:

$$\begin{cases} F_{XY}(x,y) = C(u,v) \\ u = F_X(x) \\ v = F_Y(y) \end{cases} \tag{1}$$

where $C(\cdot,\cdot)$ denotes the Copula function, and F_X, F_Y are the marginal cumulative distribution functions (CDFs) of return series X and Y, respectively.

3.1.1 GARCH model for marginal distributions

Due to its parsimony and effectiveness in capturing long-memory volatility dynamics, the GARCH(1, 1) -t model is employed to estimate the marginal distributions. This specification is particularly suitable for capturing the persistence of volatility resulting from event-driven shocks.

The return equation $\gamma_{i,t}$ is specified as:

$$\gamma_{i,t} = \mu_i + \varepsilon_{i,t} \tag{2}$$

$$\varepsilon_{i,t} = \sigma_{i,t} z_{i,t}\ ,\ z_{i,t} \sim t(v_i) \tag{3}$$

The conditional variance equation is:

$$h_{i,t|t-1} = \omega + \alpha\varepsilon^2_{i,t-1} + \beta h_{i,t-1|t-2} \tag{4}$$

where ω represents the long-term average volatility; α capture s the short-term impact of lagged return shocks (ARCH effect); and β reflects the persistence of past volatility (GARCH effect). All three parameters are subject to estimation, and must satisfy the condition $\omega > 0$; $\alpha,\beta \geq 0$ and $\alpha + \beta < 1$ to ensure stationarity. The degrees of freedom parameter v_i in the Student's t-distribution allows for heavy-tailed error distributions. Using this model, we obtain the standardized residuals and marginal CDF for both indices.

$$u_t = F_1(\gamma_{1,t}; \phi_1) \tag{5}$$

$$v_t = F_2(\gamma_{2,t}; \phi_2) \tag{6}$$

3.1.2 Time-varying symmetrized joe-clayton copula (sjc copula)

A growing body of empirical evidence indicates that financial series rarely exhibit symmetric tail dependence (Patton, 2006). The SJC Copula allows for asymmetric tail dependence and permits the upper and lower tail dependence coefficients to evolve over time.

The Copula distribution function is defined as:

$$C_{SJC}(u,v|\tau^U,\tau^L) = \frac{1}{2}[C_{JC}(u,v|\tau^U,\tau^L) + C_{JC}(1-u,1-v|\tau^U,\tau^L) + u + v - 1] \tag{7}$$

where τ^U and τ^L denote the time-varying upper and lower tail dependence coefficients, which are parameterized using logistic function $\Lambda(x) \equiv (1+e^{-x})^{-1}$.

$$\tau_t^k = \Lambda(\omega_u + \beta_u \tau_{t-1}^k + \frac{\alpha_k}{m}\sum_{i=1}^{m}|u_{t-i} - v_{t-i}|),\ k \in \{U,L\} \quad (8)$$

where a rolling window of m trading days is used to estimate dynamic dependence, with $C_{JC}(u,v|\tau^U,\tau^L) = 1-[1-\{[1-(1-u)^\kappa]^{-\gamma} + [1-(1-v)^\kappa]^{-\gamma} - 1\}^{-\frac{1}{\gamma}}]^{\frac{1}{\kappa}}$, $\kappa = \frac{1}{\log_2(2-\tau^U)}$, and $\gamma = -\frac{1}{\log_2(\tau^L)}$.

3.2 Parameter estimation

Under the assumption that both the marginal cumulative distribution functions and the Copula function are continuous, the joint probability density function can be derived as follows:

$$f(\gamma_{1,t},\gamma_{2,t}) = c(u_t,v_t;\theta) f_{1,t}(\gamma_{1,t};\phi_1) f_{2,t}(\gamma_{2,t};\phi_2) \quad (9)$$

where $c(\cdot)$ denotes the Copula density function and θ represents the set of Copula parameters. Parameter estimation is conducted via the Inference Function for Margins (IFM) method, which involves a two-step maximum likelihood estimation procedure: first estimating GARCH-t parameters, then SJC Copula parameters.

3.3 Event effect decomposition

3.3.1 Test of independent effects

We use the Wald test to assess whether the tail dependence coefficients differ significantly before and after each event. Let τ_{pre} and τ_{post} be the tail dependence values in two adjacent sub-periods. The null hypothesis $H_0{:}\tau_{pre} = \tau_{post}$ is tested against the alternative.

The Wald statistic is computed and compared to the critical value: $\chi^2_{0.95}(1) = 3.841$. If the test rejects H_0 at a given significance level, this indicates that the observed change in tail dependence is statistically significant and attributable to the event, rather than to random fluctuations.

3.3.2 Test of synergistic effects

To test for nonlinear interaction effects between policy shocks and technology shocks, we construct two dummy variables, $D_{1,t}$ and $D_{2,t}$, which represent the occurrence of the respective events. We then estimate the following regression model that incorporates their interaction term:

$$\tau_t = a_0 + a_1 D_{1,t} + a_2 D_{2,t} + a_3(D_{1,t} \times D_{2,t}) + \sum_{k=1}^{K}\phi_k \tau_{t-k} + \varepsilon_t \quad (10)$$

A significantly positive coefficient for a_3 indicates the existence of synergistic effects, i.e., the combined impact of both shocks on tail dependence exceeds the sum of their individual effects.

4 Data and variables

This study utilizes daily opening and closing prices of the Hang Seng TECH Index (HSTECH) and the NASDAQ Composite Index (IXIC) from September 19, 2023, to April 30, 2025. The data are obtained from the Wind Financial Terminal. After removing missing observations and excluding non-overlapping public holidays in China and the United States, a total of 384 synchronized daily observations are obtained for each index.

To address non-stationarity inherent in price series, logarithmic daily returns are computed based on closing prices as follows:

$$r_t = \ln(\frac{P_t}{P_{t-1}}) = \ln P_t - \ln P_{t-1} \quad (11)$$

All return series are then standardized and used as inputs for subsequent empirical modeling.

To investigate the independent and joint effects of heterogeneous shocks on tail dependence, we focus on two major exogenous events:

Policy Event — U.S. Federal Reserve Rate Cut:

On September 19, 2024, the Federal Reserve announced a 50 basis point reduction in the federal funds target range to 4.75%–5.00%, marking its first rate cut since March 2020.

Technology Event — Launch of DeepSeek-R1:

On January 20, 2025, DeepSeek released its open-source reasoning model DeepSeek-R1, representing a major technological breakthrough in China's generative AI sector.

Based on these events, the sample is divided into three sub-periods to capture potential regime shifts:
· Baseline Period: September 19, 2023 – September 18, 2024
· Policy Shock Period: September 19, 2024 – January 19, 2025
· Technology Overlay Period: January 20, 2025 – April 30, 2025

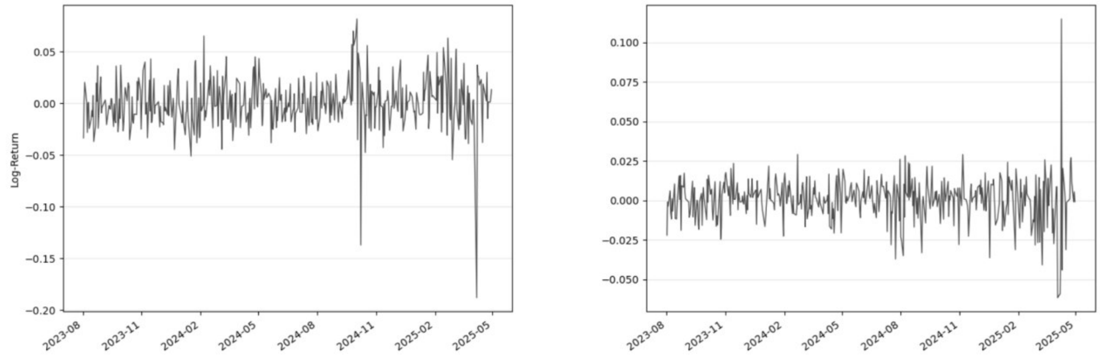

Figure 1 Log Returns of HSTECH (left) and NASDAQ (right)

Table 1 Descriptive Statistics

series	mean	std	skew	kurtosis	J-B	ADF	ARCH
HSTECH	0.0003	0.025	-1.087	19.85	1761.877***	-20.449***	5.410***
NASDAQ	0.0005	0.014	0.559	11.621	2356.851***	-21.682***	4.739***

ADF: Augmented Dickey-Fuller test; J-B: Jarque-Bera test for normality; ARCH: Lagrange Multiplier test for ARCH effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The descriptive statistics indicate that both indices exhibited relatively low and comparable average returns over the sample period. However, their skewness differs: the HSTECH index exhibits left-skewness, suggesting a higher likelihood of negative extreme returns, whereas the NASDAQ index shows right-skewness.

The Jarque-Bera test strongly rejects the null hypothesis of normality for both series at the 1% significance level, consistent with previous studies on financial return distributions. Although log returns help stabilize the series, we further apply the Augmented Dickey-Fuller (ADF) test to verify stationarity. The significant ADF test statistics confirm that both return series are stationary.

Moreover, the presence of ARCH effects, as evidenced by the ARCH test results, supports the adoption of GARCH-type models for capturing volatility clustering. Collectively, these findings justify the application of the GARCH-t model for estimating the marginal distributions of the two indices.

5 Empirical results

5.1 Marginal distribution modeling (garch model)

To avoid convergence warnings during model estimation, we scale the return series by a factor of 100 to convert them into percentage returns.

Extensive empirical evidence shows that the GARCH(1, 1) model adequately captures the marginal distributions of most financial time series. Given the non-normality of the return distributions and relatively low volatility, we adopt the GARCH(1,1)-t model under the assumption of zero mean returns.

Table 2 GARCH(1,1)-t Model Estimation Results

Index	ω	α	β	df	Log-Likelihood	α + β
HSTECH	0.731***	0.105**	0.761***	6.334***	-920.100	0.866<1
NASDAQ	0.158*	0.109**	0.800***	6.912***	-674.505	0.909<1

The estimation results show that both the ARCH coefficient (α) and the GARCH coefficient (β) are statistically significant at the 5% level, indicating the model's strong explanatory power for volatility dynamics. The condition α+β<1 is satisfied for both indices, implying model stability.

The NASDAQ index displays relatively less significant parameter estimates, suggesting greater uncertainty in its long-term volatility. In contrast, the HSTECH index has a significantly larger ω, confirming higher average volatility and greater market uncertainty, likely reflecting its emerging market characteristics.

Both models yield degrees of freedom in the range of 6 to 7, confirming the presence of heavy tails and validating the use of the Student ' s t-distribution in capturing extreme observations.

To assess model adequacy, we extract the standardized residuals from the GARCH models and conduct the Ljung-Box test. Results show no significant autocorrelation within 10 lags. Meanwhile, the ACF and PACF plots further confirm that all autocorrelation coefficients fall within the 95% confidence bands, indicating that the GARCH(1,1)-t model effectively captures the dynamics of the return series.

5.2 Time-varying SJC copula estimation

According to Sklar's Theorem, the input variables for a Copula function must follow a uniform distribution. Therefore, we apply the Probability Integral Transform (PIT) to the standardized residuals from the GARCH model, mapping the original variables into the unit interval [0,1]. The Kolmogorov–Smirnov test confirms that the transformed series follow a uniform distribution, validating their suitability for Copula modeling.

Table 3 Euclidean Distances of Constant Copula Models (Kernel Density Based)

	Gaussian	Student's t	Clayton	Gumbel	Frank
d	15.762	15.928	**14.726**	**15.358**	15.407
τ	0.154	0.160	**0.033 (L)**	**0.103 (U)**	0

τ denotes Tail Coefficient. The smaller the Euclidean distance d, the better the model performance in capturing the dependence structure.

To evaluate the best-fitting Copula structure, we estimate five types of constant Copulas: Gaussian, Student's t, Clayton, Gumbel, and Frank. Based on kernel density estimation, we compute the lower tail dependence coefficient based on the Clayton Copula and the upper tail dependence coefficient based on the Gumbel Copula under the assumption of constant dependence structure.

However, given that financial market linkages are inherently time-varying, we employ the time-varying SJC Copula to overcome the assumption of constant dependence structure, enabling more accurate modeling of dynamic relationships between markets.

We initialize the time-varying Copula using the constant tail dependence coefficient and parameter values suggested by Patton (2006), then estimate the optimal parameters using Maximum Likelihood Estimation.

Table 4 Estimates for Time-Varying SJC Copula Parameters

	ω	α	β
Upper Tail	-0.519	-6.320	2.611
Lower Tail	0.655	-1.038	-11.731

The estimated coefficients confirm that both upper and lower tail dependence parameters are time-varying. Notably, upper tail dependence evolves more gradually, while lower tail dependence exhibits stronger time sensitivity, likely reflecting asymmetric investor reactions to downside risk versus upside gains.

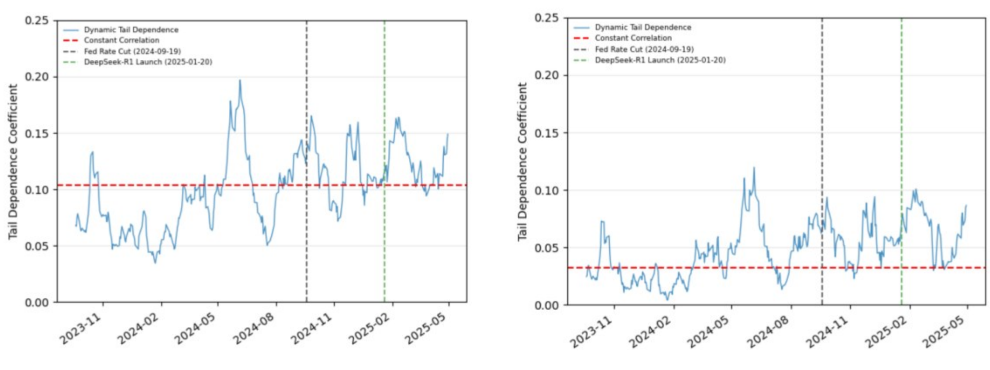

Figure 2 Time-Varying Tail Dependence Coefficients (Left: Upper Tail, Right: Lower Tail)

Table 5 Average Tail Dependence Across Sub-Periods

Period	Baseline	Policy Shock	Technology Overlay
Upper Tail	0.088	0.115	0.124
Lower Tail	0.040	0.056	0.065

Visual inspection of the tail dependence graphs reveals significant fluctuations in upper tail dependence following each major event. The average tail dependence coefficients across the three event windows show a monotonic increase: upper tail dependence rises by 1.31% and 1.35% respectively, while lower tail dependence increases by 1.40% and 1.63%, respectively during the Policy and Technology periods.

These findings suggest that both the Federal Reserve's rate cut and the release of DeepSeek-R1 have intensified the co-movement of extreme returns between the U.S. and Chinese technology stock markets.

5.3 Tests of independent and synergistic effects

To ensure the statistical significance of the observed tail dependence, we first conduct Wald test to assess whether the average tail dependence coefficients differ significantly across adjacent sub-periods. As shown in the results, both upper and lower tail dependence change significantly following both the policy and technological events, verifying that each event independently influences market co-movements.

Table 6 Wald Test Results (Independent Effects)

Comparison Periods	Wald (Upper)	Wald (Lower)
Baseline vs. Policy Shock	58.896***	110.650***
Policy Shock vs. Technology Overlay	7.070***	8.260***

Subsequently, we introduce two dummy variables representing the occurrence of the policy and technology events, respectively. A multiple regression model with lag terms and an interaction term is estimated to evaluate potential synergistic effects. The regression results are shown below.

Table 7 Regression Results (Synergistic Effects)

Variable	Intercept	D1	D2	D1D2	Lag1	Lag2	Adjusted R^2
Upper	0.007***	0.002**	0.001**	0.0128***	0.892***	0.064	0.954
Lower	0.015***	0.0008	0.001	0.0002***	1.092***	-0.279***	0.914

The regression model for upper tail dependence yields an adjusted R^2 of 0.936, indicating strong explanatory power. In contrast, the model for lower tail dependence demonstrates a weaker fit. Importantly, the interaction term (D1×D2) is significantly positive at the 1% level in both models, suggesting that the Federal Reserve's rate cut and the release of DeepSeek-R1 jointly exert a nonlinear, synergistic impact on tail risk interdependence between the two markets.

These results indicate that, following the policy shock, tail dependence between the two markets initially declined in the short term. However, over a longer horizon, the tail dependence during the policy shock period remains significantly higher than that in the baseline period. In contrast, the technological event leads to a sharp short-term increase in tail dependence, but the impact appears less persistent, suggesting a shorter-lived effect.

6 Conclusion

6.1 Main findings

This study examines the dynamic co-movements between Chinese and U.S. technology stock markets from September 2023 to April 2025, focusing on the impact of two major exogenous shock: the Federal Reserve's interest rate cut and the launch of the DeepSeek-R1 AI model. The empirical results show that the combined effect of these events significantly strengthens the tail co-movements between the two markets.

Specifically, the HSTECH Index, representing an emerging market, exhibits higher baseline volatility, whereas the NASDAQ Composite Index, as a mature market, shows lower baseline volatility but more persistent responses to external shocks. Both events primarily impact the upper tail of the return distribution, and their effects are asymmetric: the policy shock triggers a more immediate increase in tail dependence, while the technological shock contributes to a gradual but sustained rise in co-movements.

However, this study is constrained by its limited sample period. Future research should incorporate longer time spans to examine the robustness and generalizability of these findings.

6.2 Implications

6.2.1 For policymakers

Regulators should pay attention to the contagion channels among technology sectors, particularly under concurrent monetary policy shifts and technological innovations. Strengthening early-warning mechanisms and enhancing cross-border regulatory coordination are essential to mitigate the complex evolution of tail risks.

6.2.2 For risk management by investors

In an era of global financial integration, trade frictions are inevitable, and breakthroughs in frontier technologies such as generative AI not only stimulate sectoral growth but also heighten the risk of cross-border interdependence.

Enterprises must strike a balance between transparency in technology disclosure and market stability. Investors, in turn, should diversify portfolios and actively manage tail risk during periods surrounding major policy or technological developments to avoid extreme losses.

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